Explaining Aggregate Consumer Delinquency Behaviour over Time

John Banasik

Jonathan Crook

Credit Research Centre, University of Edinburgh

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Correspondence: j.crook@ed.ac.uk

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1. Introduction

The aim of this paper is to explain aggregate delinquency activity of consumer debt over time. Aggregate delinquency is of importance to financial institutions and consumers alike. An increase in total consumer delinquency would, *ceteris paribus*, cause a decrease in banking sector profits and may increase the need to increase interest rate margins to compensate for increased risk. Alternatively institutions may increase their capital adequacy ratios. A significant increase in delinquencies may cause lenders with low capital adequacy ratios to become insolvent causing widespread failures by contagion. In fact the new Basel Accord allows banks to use their own models to forecast future probabilities of default, but they must use data over a five year period and so must take into account variations in both the probabilities of default, the proportion of debt which is written off and the estimated exposure given default over the economic business cycle. Regulators, both national and international (for example the BIS), keen to avoid banking crises will observe delinquency rates aware that there may be a need to impose minimum adequacy ratios if they do not exit, or to increase them if they do exist already. Actions by lenders to avoid banking crises will impact directly on consumers, for example, by reducing lending activity or raising interest rates.

2. The Literature

There is a growing literature on why a borrower may default on a debt. Essentially two approaches exist. First, an 'ability to pay' hypothesis that a borrower will fail to pay on time when an income or expenditure shock occurs that was not expected at the time the loan was taken out. The causes of such shocks include unpredicted loss of job, marital breakdown, family bereavement, health problems, increases in interest payments on loans, and so on. Secondly, the 'strategic default hypothesis' whereby when a loan is used to buy a real asset (for example a house), and if the capital market is perfect with no transactions costs or reputation effects, a borrower would increase his wealth if he defaulted on a loan when the value of it was greater than the value of the asset (Kau et al 1995). In fact and more realistically, if transactions costs do exist and default does reduce the chance of a borrower gaining future loans, the option to default will not be exercised until the debt is somewhat greater than the asset value because default removes the option to default or repay in the future (Kau et al 1994). Lambrecht et al (1997) point out that for some the costs of default are higher than for others. For example those to whom access to debt is particularly important will experience a higher cost if default reduces the chance of borrowing in the future. According to the Permanent Income Hypothesis these are individuals who expect their income to rise in the future (Deaton 1992). Note also that unlike a Chapter 7 bankruptcy declaration in the United Sates, a default in some countries, for example the UK, does not prevent creditors pursuing for the debtor for repayment. In such countries this latter point removes the reason for strategic default.

When considering aggregate default rates over time in the United States, several explanations have been advanced. Observing the increase in the credit card delinquency rates between 1994 and 1997 Gross and Souleles (2002) propose two explanations. First that the proportion of borrowers that were of low risk increased and it has been these borrowers who defaulted. Second, that borrowers 'have become more willing to default', given their risk characteristics, because the social stigma of default and loss of future credit supply have declined.

The empirical evidence has come in the form of cross section and time series studies. We begin with the former, the majority of which are duration models. Gross and Souleles, op cit, estimated duration models using a panel of over 200,000 credit card borrowers. They found that the unemployment rate in the county of residence, the per capita income and house prices in the region were not significantly related to delinquency, and together with measures of borrower risk they could only explain a small proportion of changing delinquency rates over time. The residual was tentatively ascribed to the trend of reduced stigma. However, as we show in the next section, FCIC data suggests that if the period under consideration is extended to between 1992 and 2004, the delinquency rate on credit card debt has, if anything, trended downwards and the same is true of total consumer debt. Agarwal et al (2003) also use a duration model and panel data for credit card holders for 1994-2001. They found the probability of a credit card holder missing three consecutive payments in a particular period, given the card holder's predicted level of risk, was increased if the unemployment rate in the county or State of residence was higher three months, and especially six months earlier, but that the change in the unemployment rate had no effect. Account balance three months earlier also positively affected the hazard rate.

Turning to mortgage debt, Lambrecht et al (1997) used a survival model applied to 5272 borrowers who defaulted on their mortgages in the UK to distinguish between the ability to pay and strategic default hypotheses. They found evidence more in favour of the ability to pay argument that the strategic default hypothesis. But none of the variables they included varied over time. Deng (et al 1993) estimated a competing risks model of prepayment and default, for mortgages granted between 1976 and 1983, to investigate the extent to which the hazard rate can be explained by the strategic default hypothesis. For default to be optimal in the presence of transactions costs the put option must be in the money and trigger events like divorce or unexpected unemployment must occur. The time varying annual divorce rate and quarterly unemployment rate in the State of residence were both found to significantly affect the probability of default, as was the probability the put option was in the money. Using a sample of mortgage loans in Singapore, Teo (2004) tested an eclectic range of hypothesised determinants of the hazard rate. He found that whilst neither characteristics of the property bought, nor of the borrower, explained the rate, those of the mortgage and of the macroeconomy did. Teo's evidence may be interpreted as supporting both the ability to pay and strategic default hypotheses. In the first case he found evidence that the greater the proportion of the house's price that was financed from compulsory savings (and so the greater availability of cash savings to maintain payments) lowered the hazard rate. Similarly the greater the increase in the mortgage rate between loan origination and delinquency date the greater the probability of delinquency. Relating to strategic default he found that the higher the mortgage rate over the opportunity cost of funds, the higher the stock price index and the greater the increase in property prices, the greater the hazard rate. However, Teo's study is limited by a small sample size and collinearity.

All of the cross section studies have the weakness that the time spans over which defaults are modelled are relatively short and they do not cover an entire business cycle. It is therefore questionable whether there is sufficient variation in the macroeconomic variables over time to accurately estimate their effect. A limited number of studies have considered time series data on aggregate default rates which do cover much longer periods. Whilst these studies do not explain inter-borrower variation in default probabilities, the survival models (above) do not include data on the occurrence of borrower unemployment or changes in income.

With one exception, time series studies relate only to types of consumer credit and none relate to mortgages. One of the earliest studies is by Sullivan (1987). She used data from 1975 to 1986 to find that the debt burden (ratio of debt outstanding to disposable income), the growth rate of debt and the share of total consumer debt issued by banks, explained levels of delinquency on bank issued instalment credit. For bank cards the debt burden, growth rate and unemployment rate were correlated with delinquency and the picture was very similar for auto loans. The debt burden was taken to indicate the ability of households to repay debt whilst market share and growth were taken as indicators of banks' willingness to lend. However, Sullivan did not consider some important factors which one would expect to be important in the explanation of delinquency rates, for example the level of interest rates, and there is evidence her empirical model may be misspecified. More recently, Ausubel (1997) argued that the trend in credit card delinquency, though not necessarily *total* consumer debt delinquency, had been upwards over the period 1971-96. He observed visually that over this period the level of the credit card charge off rate was negatively correlated with the growth rate of GDP and the credit card delinquency rate was negatively correlated with the growth rate of the US payroll employment. In both cases the changes in the charge-offs and in delinquencies led changes in the indicators of the state of the economy. Ausubel also noted that increases in charge offs may be caused by changes in the interest rate spread on credit cards and vice versa. This is an informative study but it does not estimate an econometric model to explain default behaviour. Ausubel also alludes to the possibility that if direct mailings were becoming less effective over time, bank profits may have been enhanced by accepting lower risk borrowers, so subsequently increasing default rates.

Grieb et al (2001) empirically modelled bank card delinquency rates over 1981 to 1999. They found these were explained by debt to income ratios, which were taken to represent capacity to pay, with no evidence supporting the ideas that delinquency was due to job market conditions, high interest rates or high credit supply. They do, however, find evidence that borrowers defaulted on credit card debt before other types of consumer debt. However, the empirical model in their study has low explanatory power and omits the possibility that an error correction mechanism may be estimated and may be more informative than the model chosen.

The only paper looking at times series in mortgage default rates is by Whitley et al (2004). They use an error correction model to explain delinquency time series movements, but in the UK. They find the proportion of mortgage loans which are at least six months in arrears is related to mortgage income gearing, unemployment, and loan to value ratio for first time buyers. However, the lack of regression diagnostics, the imputation of quarterly data from semi-annual data, and a lack of explanation of the structure of their model limits the usefulness of these results.

Overall the literature suggests that variations over time in aggregate delinquency rates for unsecured credit are due to variations in the ability of the average borrower to make repayments and to variations in the risk distribution of borrowers due to bank lending policies. For secured lending one can add variations in the values of real assets relative to debt outstanding on them. We now turn to patterns in delinquency.

3. Patterns in Delinquency and Charge offs

Figure 1 plots delinquency and charge off rates as a percentage of debt outstanding[1] for all consumer loans extended by all US commercial banks from 1987 until 2004. During this period the trend in charge off rates is distinctly upwards whereas that of 30+ days delinquency is slightly downwards. This suggests that the average period of time which is taken before a delinquent loan is charged off has shortened, especially in the period 1997-2002. The values in 2002 Q1 where the charge off rate slightly exceeds the delinquency rate is probably due to a slightly different method of calculating the two rates and possibly different methods of applying seasonal adjustment[2].

We construct a model to explain these patterns in section 4. However, notice that patterns in delinquency occur for different reasons compared with charge offs. Missing a payment and remaining 30+ days overdue is a "decision" made by a borrower. The charging off of a debt is a decision made by a lender contingent on a prior decision made by a borrower to miss at least one scheduled payment. We might therefore expect that delinquency rates would lead charge off rates, but that is not what the data suggests. Apart from late 1992 when the peak in delinquency precedes that of charge offs by one quarter, both series have a trough in 1994 Q3and a peak in 1997 Q2 and from 2000 Q2 to 2002 Q2 the series appear to be negatively correlated.

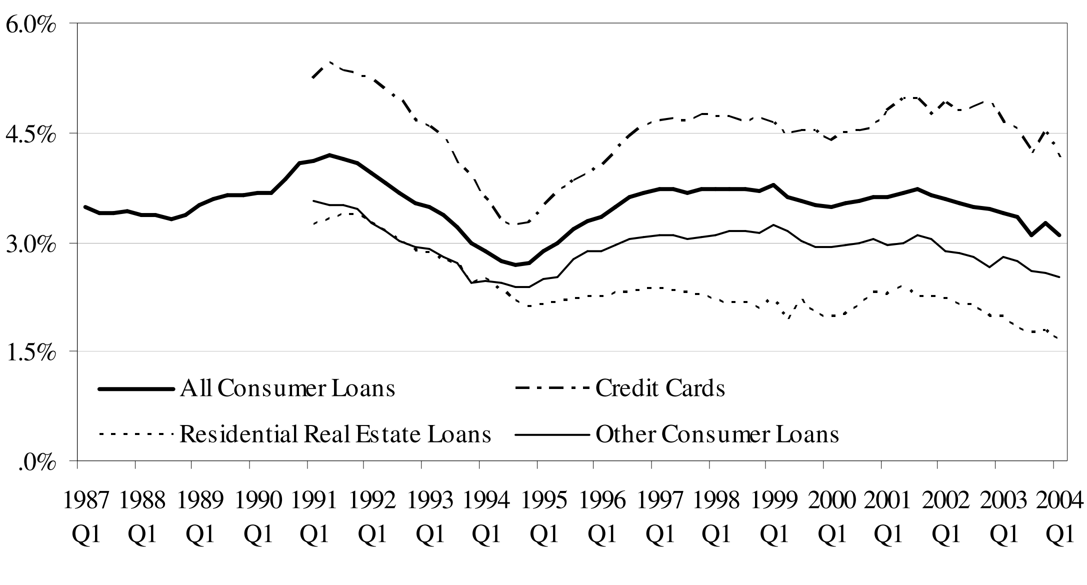


Figure 1: Seasonally adjusted delinquency rates for different loan types.

The delinquency rates for all consumer loans in Figure 1 mask different patterns in the rates for different types of loans. Note that consumer loans consist of credit card loans plus other consumer loans, residential real estate loans are separate. The trend

[1] The delinquency rate is the value of loans 30+ days overdue as a percentage of debt outstanding at the end of the quarter; the charge off rate is "are the value of loans removed from the books and charged against loss reserves, are measured net of recoveries as a percentage of average loans and annualized" (FRB).

[2] The delinquency rates were seasonally adjusted by the authors using X12. The charge off figures were adjusted by the FRB.

for all three types of loans has been downward since 1992 but the delinquency rate for real estate loans appears to have been little affected by the business cycle trough in late 1994 whilst the rate for consumer loans was substantially affected and credit card loans especially so. Perhaps surprisingly the consumer loans seem positively correlated in the mid 1990s. That is as real disposable income declined to 1995 Q4 and rose thereafter, default rates on consumer loans declined as well though they stopped mirroring income from about mid 1997. One possible explanation for this is that as the level of income falls so does the demand for debt and so the less credit worthy find that repayments relative to income decline and they are less likely to miss a payment or possibly to stay overdue. If there is a critical level of debt outstanding above which there are a disproportionate number of defaulters, then when income declines overdue debt will decline faster than the debt outstanding. One would expect this to apply especially to short term debt – consumer debt, especially credit card debt, than to debt where the borrower expects to repay over many years: residential debt. Of course to examine these possible explanations in detail requires that we examine the time series properties of the series, and construct a multivariate model, which we do in the next section.

4. The Model

We can think of the movement of debt between different states over time. We could represent this movement in a conventional transition matrix (see Table 1) as follows:

Table 1: Repayments transition matrix

	1	2	3	4
1	v_{11}	v_{12}	v_{13}	v_{14}
2	v_{21}	v_{22}	v_{23}	v_{24}
3	v_{31}	v_{32}	v_{33}	v_{34}
4	v_{41}	v_{42}	v_{43}	v_{44}

Where the states are: 1= No credit, 2= Up to date, 3=30+ days over due and 4= Charged off and v_{im} is the volume of credit which moves from state i in period t to state j in period t+1. We are not assuming that v_{ij} remains constant over time. Let the period of time be one quarter. Certain values of v_{im} must necessarily take on the value of zero. These are v_{12}, v_{13}, v_{14}, v_{41}, v_{42}, v_{43} and v_{44}.

The change in the stock of overdue debt consists of v_{23}, which is the volume which moves from being up to date to being 30+ over due, v_{31} and v_{32}, respectively the volume which moves from 30+ overdue to no credit or to up to date, and v_{34} which represents the volume which moves from 30+ to being charged off. Letting $d_t = v_{23}$, $p_t = (v_{31} + v_{32})$ and $c_t = v_{34}$ we can write:

$$S_t - S_{t-1} = (d_t - p_t) - c_t \tag{1}$$

where S_t = real volume of consumer debt which is 30+ days over due in quarter t.

We model delinquency rates in terms of the ability to pay hypothesis and, for loans on residential real estate, we include a variable to represent the strategic default hypothesis. Thus we assume that the volume of debt which is 30+ days overdue at the end of a quarter is correlated with the levels of nominal interest rates (r_i), the volume of debt outstanding, ccout, personal disposable income, pdi, and expectations about future income during that period. The interest rate and level of disposable income affect the ability of a borrower to repay. Expectations of higher future income may lead a borrower to wish to borrow more now and in the future and so he will not wish to risk his ability to do this by missing payments. For real estate loans we included the level of real house prices, the argument being that if house prices are low, controlling for the level of debt outstanding, the greater the proportion of borrowers for whom the value of the debt exceeds the value of the property plus transactions costs, and the greater the advantage of default, assuming the lender does not continue to pursue the debtor.

These arguments imply that the change in the stock of overdue debt, the levels of $(d_t - p_t) - c_t$, is correlated with changes in these explanatory variables. A change in interest rates or a change in disposable income, which at the level of a borrower could be the result of a catastrophe such as job loss, marital break-up, results in an increase in other level of overdue debt.

We assume the long-run relationship between the stock of overdue debt and its determinants is linear, thus we write

$$S_t = \delta + \delta' x_t + \varepsilon_t \qquad (2)$$

Estimation

The vector error correction representation of equation (2) is

$$\Delta S_t = \beta' \Delta x_{t-1} + \theta_1 (S_{t-1} - \delta_1 - \delta_2' x_{t-1}) + \varepsilon_t \qquad (3)$$

Engle and Granger showed that if variables in the x_t vector, and S_t, are integrated order 1 and if a cointegrating vector exists then there is a vector error correction representation of the model, of which equation 3 is an example, where ε_t is white noise. The expression in brackets in equation (3), the error correction mechanism, represents the deviation of S_t from its long-run value of $\delta_1 + \delta_2' x_{t-1}$. Equation 3 could be rewritten and estimated as an autoregressive distributed lag model or estimated as a vector error correction model and in principle both sets of estimated structural parameters should be the same (Patterson 2000). Because it revealed more information overtly we chose to estimate the VEC form. We therefore tested all of the variables for the order of integration and, finding them to be I(1) we proceeded to estimate the long-run relationship using Johansen cointegrating ML procedure and then to estimate the ECM representation.

In general having estimated the cointegrating relationship using equation 3, we then estimated the short-run dynamic model:

$$\Delta S_t = \alpha + \sum_{l=0}^{4} \beta_{1l} \Delta ri_{t-l} + \sum_{l=0}^{4} \beta_{2l} \Delta pdi_{t-l} + \sum_{l=0}^{4} \beta_{3l} \Delta ccout_{t-l} + \sum_{l=0}^{4} \beta_{4l} \Delta (optimism)_{t-l} + \theta_1 \left[S_{t-1} - \delta_1 - \delta_2 ri_{t-1} - \delta_3 pdi_{t-1} - \delta_4 ccout_{t-1} - \delta_5 (optimism)_{t-1} \right] \qquad (4)$$

Here we assumed the variables in the x_t vector were weakly exogenous and so included as Δx_t terms. To allow for more distant changes to affect the short-run dynamics of the model we included the first differences in the r_i, pdi, ccout and optimism variables to be lagged up to four quarters and then tested down to a parsimonious form. The variables in the cointegrating vector were selected to accord with reasonable *a priori* predictions. These were that (a) it would seem implausible that at higher levels of interest rates delinquency would be lower and (b) higher personal disposable income would result in higher delinquency.

5. Results

The data for the volume of overdue debt on consumer loans to commercial banks was estimated from the delinquency rates published on the FRB website. For total consumer loans the delinquency rate was multiplied by the volume of consumer loans, both seasonally unadjusted, and then was seasonally adjusted using the Stats Canada X12 routine. All of the variables were seasonally adjusted using X12 unless only seasonally adjusted values were available. The natural logs of all variables were then used. Unfortunately because of lack of data on the corresponding amounts of debt outstanding on credit cards, residential mortgages or other consumer loans our dependent variables for these types of loans is the delinquency rate. We could not find an interest rate for each separate type of loan for the entire period of our data. We were able to find data for credit card interest rates, mortgage interest rates and the mean rate for 24 month personal loans.

We first checked to see if the variable were stationary using a Phillips Peron test. We assumed a time trend for levels but not for first differences. The results are shown in Table 2. From this it can be seen that all variables were integrated order 1 and so their first differences were stationary.

Because of possibly different hypotheses explaining delinquency, we considered delinquency behaviour for residential real estate loans separately from that for consumer credit.

Table 2: Phillips-Perron unit root tests

	Levels (with trend)	Adjusted t-statistic	Differences (without trend)	Adjusted t-statistic
Consumer delinquency types:				
Bank credit total	Lnrdelsa	–2.068	dlnrdelsa	–5.441**
Bank credit card	Lnccsa	–1.936	dlnccsa	–5.368**
Other bank credit	Lnosa	–1.951	dlnosa	–5.366**
Mortgage loan	Lnrnsa	–1.887	dlnrnsa	–9.336**
Explanatory variables				
Consumer credit outstanding	Lnrccoutsa	–1.810	dlnrccoutsa	–4.352**
Personal loan interest rate	Lninsa	–2.266	dlninsa	–7.520**
Consumer sentiment index	Lnsent	–3.210	dlnsent	–11.121**
Personal disposable income	Lnrpdisa	–1.710	dlnpdisa	–10.992**
House price index	Lnrhpsa	–1.216	dlnrhpsa	–4.016**
Real estate credit outstanding	Lnrnoutsa	–0.811	dlnrnoutsa	–5.095**
Mortgage interest rate	Lnmisa	–3.124	dlnmisa	–6.725**
Credit card interest rate	Lnccintsa	–1.815	dlnccintsa	–5.727**

* = significant at 5% one sided test (MacKinnon)
** = significant at 1% one sided test (MacKinnon)
In all cases bandwidth 4 (Newey-West using Bartlett Kernel)

5.1. Volume of Consumer Credit

Table 3 shows the results of the Johansen cointegration tests. For the volume of delinquent consumer debt we excluded disposable income from the long-run model because when included it had an *a priori* inadmissible sign. The top panel shows both the Trace and Maximum Eigenvalue statistics reject the hypothesis of at most zero cointegrating relationships but not that there is at most one. We conclude that there is only one cointegrating relationship. Table 4 column 1 shows this relationship normalised on the volume of delinquent debt. Since the values are all in logs (except the trend) the coefficients can be interpreted as elasticities. The relationship shows that in the long-run, *ceteris paribus*, the higher is the nominal interest rate and/or the volume of consumer debt the greater is the volume of consumer debt that is 30+ days overdue. The asymptotic t-statistics suggest both are statistically significant. Whilst the optimism of households concerning their financial situation in a year's time relative to their current situation has a negative sign – the less optimistic households are, the higher is delinquency – this does not appear significant. The delinquency elasticity of the volume of debt in equilibrium is approximately the same for nominal interest rates and for the volume of debt outstanding at around 1.7.

Table 3: Johansen cointegration tests

H_0:		Trace Statistic	5% cv	Max-Eigenvalue Statistic	5% cv
	Consumer Credit				
	Total volume (Lnrdelsa) equation				Ref:vecslnrdelsatest
r = 0		82.99**	62.99	42.29**	31.46
r ≤ 1		40.70	42.44	20.98	25.54
r ≤ 2		19.72	25.32	13.9	18.96
r ≤ 3		5.82	12.25	5.82	12.25
	Lags in ECM = 4				
	Default rate on credit cards (Lnccsa) equation				Ref:vecpolnccsa
r = 0		136.77**	87.31	44.65**	37.52
r ≤ 1		92.11**	62.99	42.34**	31.46
r ≤ 2		49.77**	42.44	23.02	25.54
r ≤ 3		26.75*	25.32	16.26	18.96
r ≤ 4		10.50	12.25	10.5	12.25
	Lags in ECM = 4				
	Default rate on other loans (Lnosa) equation				Ref:vecwlnosa
r = 0		146.01**	87.31	69.17**	37.52
r ≤ 1		76.84**	62.99	36.51*	31.46
r ≤ 2		40.33	42.44	17.29	25.54
r ≤ 3		23.04	25.32	16.50	18.96
r ≤ 4		6.55	12.25	6.55	12.25
	Lags in ECM = 4				
	Residential Real Estate Loans				
	Default rate (Lnrnsa) equation				Ref:vecslnrnsatest
r = 0		82.54**	62.99	45.74**	31.46
r ≤ 1		36.80	42.44	16.86	25.54
r ≤ 2		19.94	25.32	11.98	18.96
r ≤ 3		7.96	12.25	7.96	12.25
r ≤ 4					
	Lags in ECM = 2				

* = significance at 5%; ** = significance at 1%.

The positive marginal effect of the volume of debt outstanding (conditional on disposable income and interest rates) is consistent with several possible explanations. One is that the mean and/or variance of the delinquency probabilities amongst debtors have increased. Households have (irrationally) borrowed more than they can afford to repay on time, or because lenders have accepted more risky loan applications resulting in more debt and a higher delinquency rate. Alternatively the variance of the distribution may have increased. The interest rate effect could be the result of either or both of two factors. First, there is the lower ability of people to repay debt. Secondly, the adverse selection effect (Stiglitz and Weiss 1981) that at higher interest rates the lower the proportion of applicants that are good repayers.

Table 4: Cointegrating vectors (normalized)

Dependent variable (delinquency)		Consumer credit			Residential
		Total Volume (lnrdelsa)	Credit cards Rate (lnccsa)	Other Rate (lnosa)	Real estate Rate (lnrnsa)
Independent variable					
Personal loan interest rate	lninsa	–1.621403		2.953059	9.532144
		(5.372)**		(6.855)**	(7.943)**
Credit card interest rate	lnccintsa		.864145		
			(3.104)**		
Consumer credit outstanding	lnrccoutsa	1.826186			
		(7.675)**			
House price index	lnrpdisa		–1.013113	–4.416582	–5.975381
			(–1.052)	(–3.967)**	(–2.735)**
Consumer sentiment index	lnsent	–.364194	–3.937148	–1.513997	–6.809677
		(–1.206)	(–6.600)**	(–3.152)**	(–6.112)**
	Trend	.001714	.026636	.047222	.081932
		(1.969)	(2.594)**	(4.750)**	(4.015)**
	Constant	–12.93189	21.32306	17.09908	30.50182
	Ref:	vecs1lnrdelsa	vecpb1lnccsa	vecwlnosa	vecs1lnrnsa

Asymptotic t statistics in parentheses. * = significance at 5%; ** = significance at 1%.

Columns 2 and 3 of Table 5 show the short-run dynamic equation after variables have been removed on the basis of t-statistics and *a priori* expectations and assuming all of the independent variables are weakly exogenous on explaining the volume of delinquent debt. The error correction term is highly significant and negative meaning that the greater the amount by which the volume of debt in default exceeds its long-run value in one quarter, the larger the decrease in delinquent debt in the next quarter, which is consistent with expectations. The value implies that 33.6% of the deviation of delinquent debt from its equilibrium value is removed in the next period. Notice also that increases in current interest rates and in debt outstanding are associated with increased default debt whilst an increase in consumer optimism is associated with a decrease in delinquent debt. A change in disposable income appears initially to have no statistically significant independent effect, though it has the expected sign. Increases in defaulted debt are not generally associated with changes in optimism about family income in previous periods. This is at least consistent with delinquency being the result of unexpected income decreases. The lagging structure on interest rates is interesting in that an increase in the interest rate in the previous period results in a decrease in delinquent debt in the current period. The same applies to the stock of consumer debt outstanding. One possible explanation of the interest rate effect may be that an increase in interest rates in the previous period results in a decrease in the volume of debt held and, even without any change in the delinquency ratio, in the volume of debt which is delinquent in the current period. The explanation for the effect of the lagged stock of debt is unclear.

Figure 2 shows the observed volume of overdue consumer debt and the predicted amounts. Within sample the model predicts relatively poorly in the second quarter of

1993 and the first quarter of 1999 when it fails to indicate sufficiently the decrease in defaulted debt and also in early 2001 when it predicts a much greater decrease than actually occurred.

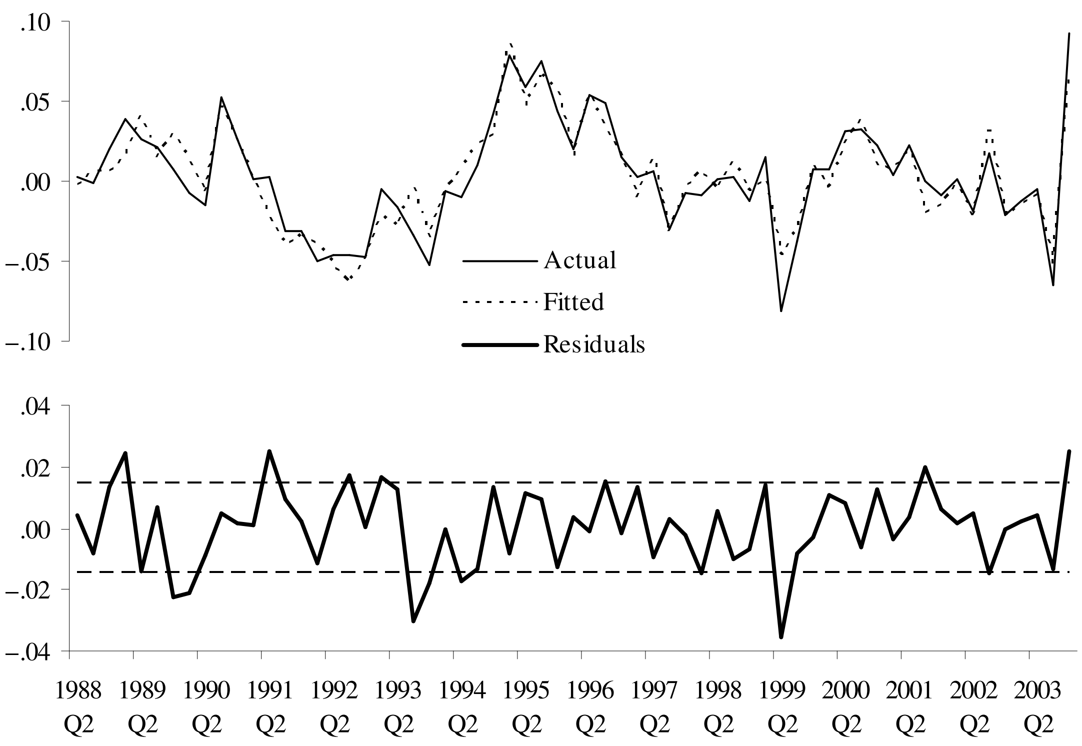


Figure 2: Changes in log volume of delinquent credit.

5.2. Delinquency Rates

We modelled the delinquency rates for two types of consumer loans separately: credit card loans and other consumer loans. These together make up total consumer loans – the variable corresponding to the volume of delinquent consumer debt in the last section. Due to data restrictions we were unable to model the volume of delinquent debt in each category. In stead the dependent variables were the volume of debt 30+ days overdue as a percentage of end-of-quarter debt outstanding. The model followed the corresponding assumptions to this above.

Credit Card Delinquency Rates

Table 3 panel 2 shows the results of the Johansen cointegration tests for the credit card delinquency rate. The Trace statistic suggests we can reject he null of at most three vector exist, whereas the Max Eigenvalue test suggests only two vectors exist. Based additionally on *a priori* reasoning we conclude that two vectors exist. Theoretical reasoning suggests that two endogenous variables in this system are the delinquency rate and consumer debt outstanding rather than the credit card interest rate, income or optimism. To identify the parameters in each vector we restrict the parameter of the endogenous variable to be zero. The parameters of the cointegrating vector for the delinquency rate are shown in Table 4 column 3.[3] The asymptotic t-

[3] The parameters of the contegrating vector for consumer debt oustanidng in this sytem are available from the authors on request.

statistics suggest the effects of the interest rate and sentiment are statistically significant and the marginal effect of the trend is positive.

Table 5: Short-run dynamic equations

Dependent Variable:	dlnrdelsa		dlnccsa		dlnosa	
Estimation Period:	1988(2) – 2003(4)		1992(2) – 2003(4)		1991(4) – 2004(1)	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Independent Variable						
Δ *dependent variable*						
ddepvar(–1)	.258410	2.698**	.093917	.700	–.092962	–.904
ddepvar(–2)			.428535	2.893**	–.293627	–2.830**
ddepvar(–3)			.115665	.956		
ddepvar(–4)	.202159	2.154*	–.172671	–1.482		
Δ *personal loan int. rate*						
dlninsa	.221353	2.192*				
dlninsa(–1)	–.529605	–4.546**			–.448054	–2.871**
dlninsa(–2)						
dlninsa(–3)						
dlninsa(–4)	–.451043	–3.435**				
Δ *credit card int. rate*						
dlnccintsa						
dlnccintsa(–1)						
dlnccintsa(–2)						
dlnccintsa(–3)			.516382	2.243*		
dlnccintsa(–4)						
Δ *cons credit outstanding.*						
dlnrccoutsa	1.173960	7.090**			.557443	2.476*
dlnrccoutsa(–1)	–.858526	–4.284**	–1.364601	–4.232**	–.312055	–1.508
dlnrccoutsa(–2)			–1.462336	–4.713**		
dlnrccoutsa(–3)			–.677485	–2.185*		
dlnrccoutsa(–4)	–.900851	–4.619**	–1.194325	–4.207**		
Δ *real personal disp inc.*						
dlnrpdisa	–.159617	–.854				
dlnrpdisa(–1)	–.182066	–.788	–.846975	–1.707	–1.132623	–3.053**
dlnrpdisa(–2)			1.522021	2.877**	–1.767030	–5.141**
dlnrpdisa(–3)	.601362	2.588*	1.879504	3.174**		
Δ *(log) optimism*						
dlnsent	–.270398	–4.503**	–.338003	–2.229*		
dlnsent(–1)			1.249800	5.519**		
dlnsent(–2)			.976731	5.846**		
dlnsent(–3)			.913309	5.208**		
dlnsent(–4)			.740584	4.375**		
error correction						
ecmvecslnrdelsa(–1)	–.336243	–8.854**				
ecmvecp1lnccsa(–1)			–.518357	–6.856**		
ecmvecp3lnrccoutsa(–1)			.565412	3.114**		
ecmvw1lnosa(–1)					–.196980	–5.195**
ecmvecw2lnrccoutsa(–1)					.571495	7.599**
Adjusted R^2	.823260		.766076		.651158	
DW	1.988687		2.042258		1.839576	
Durbin's h alt. =	–.269224		–.126608		.659655	
Jarque-Bera $\chi^2(2)$	1.216184		.002387		.310233	
RESET2 $\chi^2(1)$	.073841		.280189		.071281	
LM het. Test$\chi^2(1)$	.616331		.129038		.297544	
Ref:	vecsy2lnrdelsa		vecp7lnccsa		vecw3lnosa	

* = significance at 5%; ** = significance at 1%.

Table 5 column 4 and 5 show the estimated parameters of the short-run dynamic model. We included both difference in the credit card rate and in he 24 month personal loan rate at the beginning of the testing down procedure since it seemed plausible that either of both rates may have an effect but the testing down procedure suggested that, surprisingly, the interest rate effect was not due to changes in rates on credit card loans. In fact, as Table 5 shows, the only detectable effect of a change in interest rates was in terms of the personal loan rate and then only with a lag of three quarters. Current consumer debt outstanding had no discernable effect on credit card default rates whereas increases in debt in previous quarters reduced delinquency rates. Increases in disposable come in the previous quarter reduced delinquency rates, although this is significant only at 10%, and previous increases increased delinquency rates. This may be due to higher income causing individuals to use their credit card more and take more debt than subsequently they can service on time. Reduced optimism in the current quarter results in greater default rates but prior to this greater optimism has the same effect. Again this may be due to card holders taking on more debt than they can afford. The size of the adjustment coefficient on the cointegrating vector, –0.518357, implies that over half of the deviation from the long-run value is removed in the following quarter. Notice also hat part of the change in credit card delinquency rates is due to deviation from equilibrium in the level of *consumer credit outstanding* in the previous quarter (ecm). Put another way, if the level of consumer debt outstanding in the previous quarter is above its equilibrium level, credit card delinquencies increase in the following quarter.

Other Consumer Debt Delinquency Rates

For other consumer loans the interest rate used was the 24 month personal loan interest rate. The cointegration tests and shown in Table 4 panel 3 and agree that there are two cointegrating relationships. Again the same *a priori* reasoning as above suggests the two endogenous variables in this system are the delinquency rate and consumer debt outstanding. Restricting the parameter on debt outstanding in the delinquency equation to zero and vice versa for the debt equation, the estimated cointegrating vector for delinquency rates on other consumer loans is given in Table 4 column 4. The estimates suggest that the equilibrium delinquency rate for other consumer loans increases with the personal loan interest rate, decreases in personal disposable income goes up and decreases if households become more optimistic about their financial situation in a year's time. The delinquency rate is also trended upwards *ceteris paribus*.

Notice that the interest rate elasticity for the default rate on other loans is much higher than for credit card and the income elasticity is also much higher for other loans. This could reflect the relative size of the minimum payment for each type of debt or possibly by different methods of payment: many borrowers have arrangements with their bank to automatically pay the monthly minimum payment on credit card debt, whereas the payment mechanism for other consumer loans may be more heterogeneous because the sources of supply are so varied.

The short-run dynamic model (Table 5 columns 6 and 7), after testing down, show that no current effect of changes in the interest rate was detected and increases in the interest rate in the previous quarter increased the default rate – possibly due to increasing debt outstanding. An increase in current debt outstanding does increase the default rate, however changes in current income had no separate effect. The adjustment coefficient on the error correction term shows that 20% of the deviation from equilibrium was achieved in any one quarter: less than half of the rate for credit card delinquency. Delinquency returns much more quickly to equilibrium for credit card loans than for other consumer loans.

6. Residential Real Estate Loans

When estimating the cointegrating vector for residential loans we experimented with the inclusion of the fixed rate mortgage interest rate and also with a real house price index, the latter to take account of the strategic default hypothesis. Inclusion of the real house prices index resulted in either *a priori* inadmissible signs and/or elasticities of implausibly high magnitudes. Excluding the house price index but including the interest rate on fixed rate mortgages also caused many of the variables to have implausible signs suggesting an inappropriate vector had been found. Further, since most US households have fixed rate mortgages rather than variable rate mortgages it is unlikely that a change in this rate would affect many borrowers in the long-run. We therefore included the interest rate on personal loans on the argument that an increase in this rate would reduce the ability of mortgage holders to pay their personal loans and their mortgages. When we omitted the house price index and also the stock of consumer debt outstanding and the mortgage interest rate, so that our hypothesised long-run relationship contained just the 24 month personal interest rate, real personal disposable income and optimism (plus trend), we obtained just one cointegrating relationship, as shown in Table 3 panel 4, with *a priori* acceptable signs and magnitudes. This relationship is shown in Table 4, column 5. This means we were unable to detect a meaningful long-run relationship between the delinquency rate on residential real estate loans and the level of real house prices. This appears not to be consistent with the strategic default hypothesis since when house prices are relatively low one would expect more properties to have a value of less than the mortgage used to purchase them. However, evidence in favour of the hypothesis may come by finding a short-run relationship between changes in the delinquency rate and changes in house prices since when an individual takes out a mortgage, presumably they do not intend to default and it is a decrease in the value of the property relative to the debt used to purchase it that would result in an increase in the default rate. Table 4 also suggests a significant relationship between delinquency and disposable income and with consumer confidence. The positive marginal effect of the time trend could be consistent with both a possible long-run increase in the riskiness of the residential loan portfolio and/or with a greater willingness to become delinquent because of reduced stigma attached to such events. This would be consistent with the findings of Gross and Souleles (op cit).

Table 5 shows the short-run dynamic model results. Since the cointegrating vector was estimated with only two lags in the VEC we included only two lags on each variable. We also included both the personal loan rate and the fixed rate mortgage rate on the grounds that a change in either may reduce a household's ability to pay their mortgage and so increase the delinquency rate. We also included both real estate debt outstanding and consumer debt outstanding since changes in either, individually may increase repayments. We also included changes in real house prices to test the strategic default hypothesis.

The testing down procedure resulted in different final equations according to whether a house price index or a mortgage interest rate was included and so we present both sets of result. If we include the house price index, column 5, the current change was not significant and the change in the previous quarter has a sign which is inconsistent with the strategic default hypothesis. The model suggests that, if in the previous quarter house prices increase, then in the current quarter the delinquency rate also increases. This is more consistent with borrowers borrowing more than they can, *ex post*, repay. The marginal effect of an increase in the residential loans outstanding in the current period appears to be to reduce the delinquency rate and this might be explained by an increase in mortgage debt occurring when households' incomes income increase (we have controlled separately for income in the equation) and the delay until delinquency occurring being longer for mortgages than for consumer loans. The marginal effect of increases in current income is to reduce delinquency and the effect of increases in the personal loan rate is to increase delinquency. That is, if the servicing cost of consumer loans increases households miss payments on their real estate loans. This is consistent with our finding that if the volume of consumer loans currently increases, so does real estate delinquency. If we exclude house prices, columns 3 and 4 show that the expected current effect of mortgage interest rates is observed.

The adjustment coefficients suggest that 14% of the deviation of the delinquency rate from its long-run path is corrected for in a quarter. Comparison with Table 4 shows this to be considerably lower than for credit card delinquency and lower than for other consumer loans. This is consistent with homeowners trying to maintain real estate loan repayments rather than consumer loan repayments in the short term if the long term equilibrium default rate increases. Notice also that the current period elasticity of the effect of changes in disposable income (–2.0 to –2.3) is greater than for the delinquency rates on credit cards and other consumer loans where the effect was not statistically significant. This is also consistent with households trying to maintain mortgage payments rather than consumer loan payments if disposable income decreases.

Figure 3 shows the observed and predicted default rates for residential loans. Clearly the model predicted that the decline in the third quarter 2000 would occur a quarter early and it underestimates the size of the decline in the first quarter of 1999 and of the increase a quarter later.

7. Shock Responses and Forecasts

In this section we examine the effects of shocks to the independent variables on the volume of delinquent consumer debt and we compare the accuracy of forecasts derived form the short-run dynamic model with those given by benchmark ARIMA models. We consider only the volume of delinquency consumer debt because this is the only type of debt for which the volume of delinquent debt could be calculated.

The equation explaining the volume of delinquent credit implies an elaborate pattern of gradual impact to its independent variables. These variables typically each have several significant coefficients for it current and lagged values. The pair of significant lagged dependent variables together with the error correction mechanism permit an enhanced role for these lagged independent variables in their explanatory influence. Indeed the statistical significance of all three influences implies that the gradual influence of the independent variables is not simple.

Table 6: Short-run dynamic mortgage equation

Dependent Variable:	Log changes in mortgage delinquency rate (dlnrsa)			
	House prices omitted		House prices included	
Estimation Period:	1991(4) – 2003(4)		1991(4) – 2003(4)	
	Coefficient	t-stat	Coefficient	t-stat
Independent Variable				
Δ*delinquency rate*				
depvar (–1)	–.420133	–3.256**	–.508507	–4.272**
depvar (–2)	.115973	.882	.097369	.783
Δ*personal loan interest rate*				
dlninsa	.928878	3.410	1.117046	4.194**
dlninsa(–1)				
dlninsa(–2)	–.731228	–2.325*	–.722224	–2.335*
Δ*mortgage interest rate*				
dlnmisa	.245981	2.250*		
dlnmisa(–1)	–.123865	–1.043		
dlnmisa(–2)				
Δ*consumer credit outstanding*				
dlnrccoutsa	.608554	1.672	.744409	2.136*
dlnrccoutsa(–1)	–.705785	–2.075*	–.585076	–1.850
dlnrccoutsa(–2)				
Δ*real estate debt outstanding*				
dlnrnoutsa	–1.067942	–2.541*	–.972503	–2.735**
dlnrnoutsa(–1)	1.055581	2.267*		
dlnrnoutsa(–2)				
Δ*real personal disposable income*				
dlnrpdisa	–2.318966	–4.028**	–1.999367	–3.967**
dlnrpdisa(–1)				
dlnrpdisa(–2)	1.673529	3.097**	1.672594	3.085**
Δ*optimism*				
dlnsent	–.698787	–3.603**	–.527423	–2.840**
dlnsent(–1)			.380207	2.004
dlnsent(–2)	.537816	2.525*	.469973	2.388*
Δ*houseprice index*				
dlnrhpsa(–1)			3.002430	2.614*
dlnrhpsa(–2)			–1.699507	–1.620
error correction				
ecmvecslrnsa(–1)	–.135794	–5.316**	–.138110	–5.481**
Adj R^2	.622623		.652156	
DW	2.071361		2.127487	
Durbin's h alt. =	–.538427		–.606160	
Jarque-Bera $\chi^2(2)$	1.040751		2.903220	
RESET2 $\chi^2(1)$	.255427		.763131	
LM het. Test$\chi^2(1)$	1.458612		1.370434	
Ref:	vecb2lnrnsa		vecsa2lnrnsa	

All variable changes are in logs. * = significance at 5%; ** = significance at 1%.

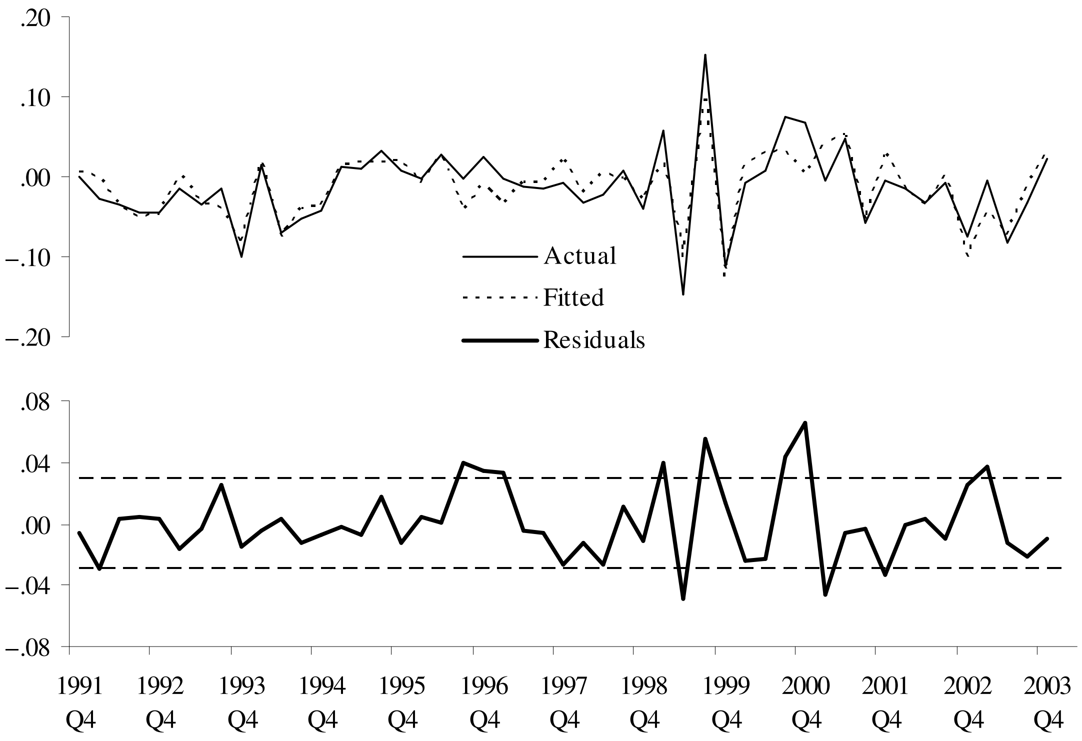


Figure 3: Changes in log default rates for residential loans.

Consider the following fragment of the equation dealing with the interest rate and lagged dependent variable alone (see Table 5).

$$\Delta \ln(\text{delsa})_t = \mathbf{.258410}\,\Delta \ln(\text{delsa})_{t-1} + \mathbf{.202159}\,\Delta \ln(\text{delsa})_{t-4} + \mathbf{.221353}\,\Delta \ln(\text{insa})_t - \mathbf{.529605}\,\Delta \ln(\text{insa})_{t-1} - \mathbf{.451043}\,\Delta \ln(\text{insa})_{t-4} + \ldots$$

Without the error correction mechanism the last three coefficients of the independent variable would be deployed by the lagged dependent variables in an infinite series of impacts as described in the top half of Table 7. The cumulative impact would be negative, suggesting perversely that a rise in the interest rate would have a negative impact on credit delinquency in spite of the increase in financial strain it would imply. The error correction mechanism reverses this influence by gradually dragging the cumulative impact toward the long-run impact of 1.621403 (see Table 4).

The calculations above illustrate the pattern of adjustment for one particular variable, but the numbers themselves are expressed in terms of log differences and so do not provide a notion of the actual impact of change on the levels of the untransformed variables. Table 8 describes the values of the variables and indicates the shock to be applied to each in turn. The shock is arbitrarily set to roughly two standard deviations of the variable. The simulation starts from a situation where all independent variables are constant at their average values, the trend variable is constant at zero, and the dependent variable is at the level implied by its long-run equation. Each variable in turn is raised by the amount of the shock and held at that higher variable indefinitely, and the dependent variable adjusts over time in the manner suggested by calculations in Table 7. Figure 4 plots the cumulative response over 20 quarters.

None of the four independent variables produce initially smooth shock responses, but all are moving smoothly toward their long-run cumulative impact within 12 quarters. The most interesting response is to the income shock which alone among the variables has a cumulative response that alternates in sign. One might expect that a rise in income would financially facilitate good repayment behaviour and thus a reduction of delinquency. This is both the initial and the (imposed) long-run effect. However, from Quarter 3 the impact turns positive and stays so for six more quarters. One may surmise from this that the influence of extra income is a tendency to overestimate the affordability of credit, inducing an uptake of credit that is very quickly becomes delinquent.

Table 7: Impact sequence on Δ ln(delsa) from a unit change of Δ ln(insa)

Dynamic impacts without error correction mechanism:

t	Additional impact	
0:	.221353 =	**.221353**
1:	–.472405 =	**– .529605** + **.258410**(.221353)
2:	–.122074 =	**.258410**(–.472405)
3:	–.031545 =	**.258410**(–.122074)
4:	–.414446 =	**– .451043** + **.258410**(–.031545) + **.202159**(.221353)
5:	–.202598 =	**.258410**(–.414446) + **.202159**(–.472405)
6:	–.077032 =	**.258410**(–.202598) + **.202159**(–.122074)

Dynamic impacts with error correction mechanism:

t	Additional impact	Previous Cumulative impact – Long-run target	
0:	.221353 =		**.221353**
1:	–.001648 =	**–.336243**(.221353–1.621403)	**– .529605** + **.258410**(.221353)
2:	.470885 =	**–.336243**(.219704–1.621403)	+ **.258410**(–.001648)
3:	.434661 =	**–.336243**(.690590–1.621403)	+ **.258410**(.470885)
4:	–.127146 =	**–.336243**(1.125250–1.621403)	**– .451043** + **.258410**(.434661) + **.202159**(.221353)
5:	.176391 =	**–.336243**(.998105–1.621403)	+ **.258410**(–.127146) + **.202159**(–.001648)
6:	.291044 =	**–.336243**(1.174495–1.621403)	+ **.258410**(.176391) + **.202159**(.470885)

Table 8: Summary statistics for variables and shocks

	Delinquency (rdelsa) ($'00 million)	Interest Rate (insa) Annual %	Credit (rccoutsa) ($'00 million)	Income (rpdisa) ($'00 million)	Sentiment (sent)
Minimum	128.62	11.72	4117.55	48.02	110.37
Maximum	202.56	15.70	5865.34	78.49	139.05
Average	173.78	13.87	4947.93	61.39	128.17
Standard Deviation	20.64	.95	444.76	9.04	6.16
Shock		2.00	900.00	17.00	13.00
Delinquency impact					
Initial		5.01	35.55	–6.23	–7.75
Long-run		40.38	58.51	.00	–10.35

The experience of credit repayment behaviour reflects the joint impact of ongoing shocks to all independent variables, and each shock response will occur before the response to previous shocks has been exhausted. Figure 2 demonstrates the model's success in coordinating these influences to track delinquency developments well and in so doing gives credibility to the predicted responses to individual variables. The comprehensiveness of the model in doing so is indicated not only by the modest magnitude of its tracking errors, but in the absence of evident pattern in these errors as indicated by the auto-correlation function (ACF) plotted in Figure 5.

Regression models are often valued for their analytical facilities in spite of inferior forecasting performance to simple models that have little explanatory content, but which manage to extrapolate well the trends and cycles in a dependent variable's behaviour. Regression models are handicapped by the need to use forecasts of the independent variables in ex-sample prediction, and thereby depend on forecasts of the independent variables to be small or to cancel. In order to assess the extent of this handicap our model estimation excluded a holdout sample of post-2003 observations. In this five-quarter period the model will have access to actual observations only to the extent that it is fitting lagged variables. Current observations and those with short lags eventually require resort to forecast values. Table 9 indicates the ARIMA models used to forecast the independent variables. ARIMA models for the dependent variable establish a benchmark performance against which the regression model can be assessed.

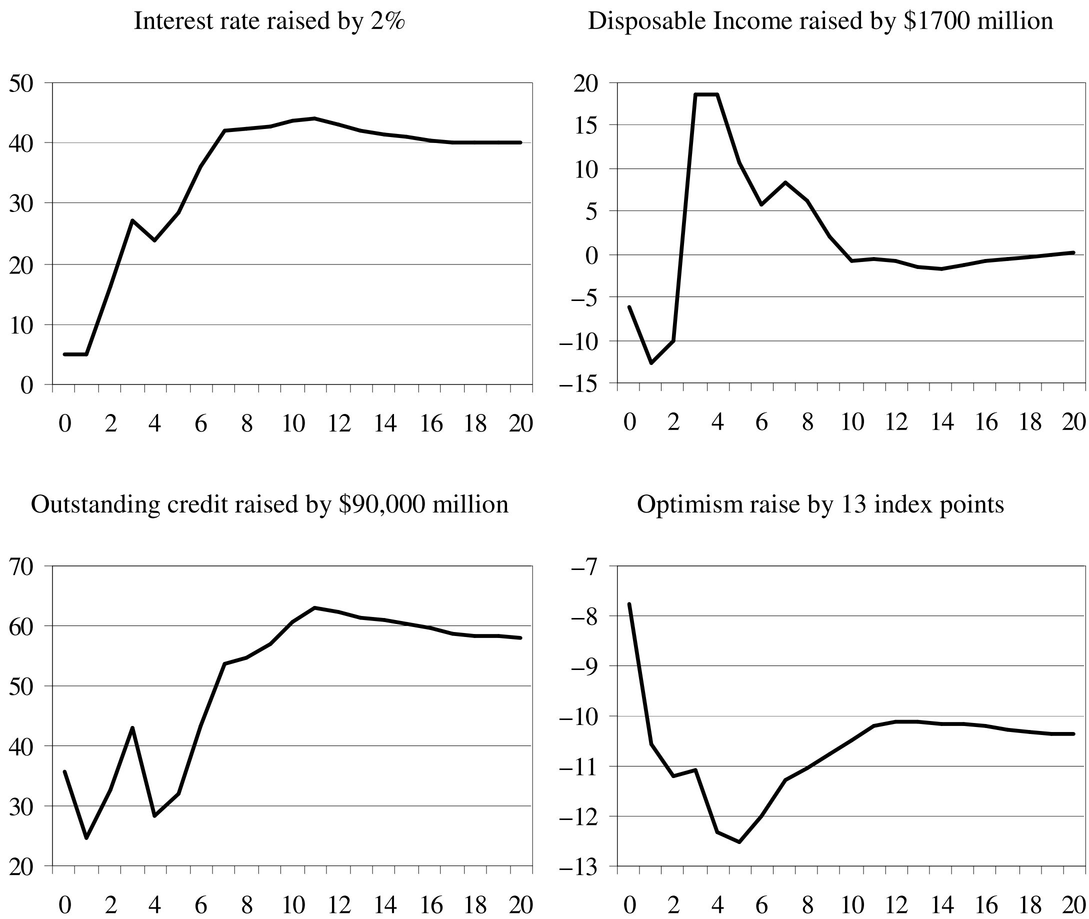
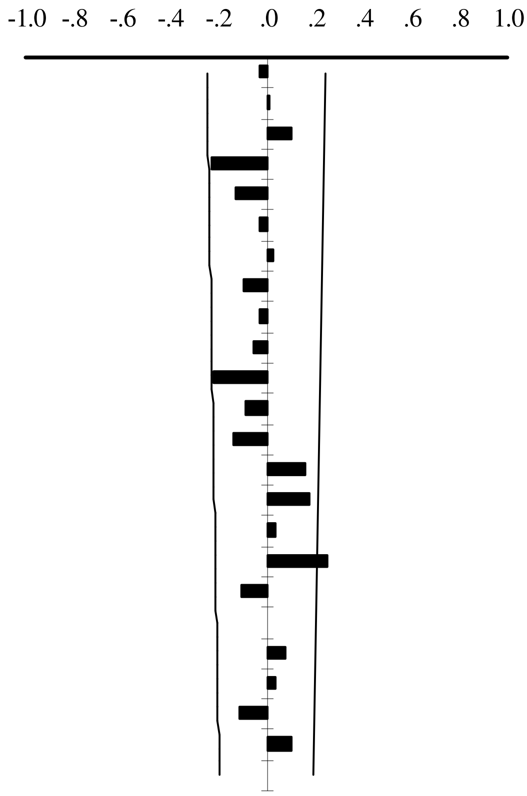


Figure 4: Cumulative impact ($'00 million) to volume of credit delinquency from various shocks in independent variables over 20 quarters.

In general the ARIMA models reported in Table 9 reflect suitable parsimony with respect to numbers of estimated coefficients, but occasionally marginally insignificant parameters are adopted as well in order to achieve a suitably impressive ACF. To the extent that missed parsimony causes suboptimal forecasts of independent variables regression model forecasts will tend to appear in a poorer light compared to benchmark forecasts.

Alternative benchmarks models were established mainly to indicate the influence of the one marginally insignificant variable that distinguishes them (the AR1 term). The omission of this variable does induce some negligible significance in the ACF pattern as indicated by the significance of the Box-Liung statistic at any point, but its inclusion avoids even any conspicuous approach to significance. To that extent its appearance is simply for cosmetic effect of demonstrating the similarity of performance between the two models. However, it also indicates the critical importance of the omission of the extra variable in the ex-sample forecasts.



Lag	Auto-Correlation	Standard Error	Box-Ljung Statistic	Prob. Value
1	–.0251	.1230	.042	.8382
2	.0144	.1221	.056	.9725
3	.1009	.1210	.750	.8614
4	–.2322	.1200	4.492	.3435
5	–.1290	.1190	5.667	.3400
6	–.0255	.1180	5.713	.4561
7	.0314	.1169	5.785	.5650
8	–.0965	.1159	6.479	.5937
9	–.0272	.1148	6.535	.6854
10	–.0563	.1138	6.780	.7460
11	–.2198	.1127	10.584	.4788
12	–.0879	.1116	11.204	.5115
13	–.1376	.1105	12.754	.4670
14	.1594	.1094	14.877	.3866
15	.1808	.1083	17.664	.2807
16	.0372	.1071	17.785	.3366
17	.2520	.1060	23.436	.1356
18	–.1040	.1048	24.421	.1417
19	.0032	.1037	24.422	.1805
20	.0800	.1025	25.032	.2002
21	.0348	.1013	25.150	.2407
22	–.1093	.1001	26.342	.2373
23	.1060	.0988	27.493	.2356
24	.0062	.0976	27.497	.2818

Black Bars denote ACF Values; lines denote two-standard error limits. Computable first lags: 62.

Figure 5: Autocorrelation Function (ACF) of Delinquency Volume Regression Model Residuals.

Table 10 reports ex-sample forecast performance for the regression model and its two benchmark competitors. These are m-step ahead forecasts that make no use of data observed in the ex-sample period. Wherever an ex-sample observation is needed of a forecast, relevant forecasts are used. For lagged independent variables in regression forecasts the regression forecasts are used, and for other independent variables the relevant ARIMA forecast is used.

Somewhat freakishly the ex-sample performance of the adopted ARIMA model exceeds that of its in-sample performance, and to that small extent its success should be discounted as simple good luck. The alternative ARIMA model is not so lucky and its performance is in fact inferior to that of the regression model. Both the regression model and the alternative ARIMA model have roughly twice the ex-sample root mean squared error (RMSE) that is observed in-sample. Both have a lagged dependent variable while the adopted ARIMA model entertains a its dependent variable twice lagged. Both encounter an initial ex-sample error that overshadows subsequent performance.

As indicated in Figure 2 the regression model exhibits a relatively large positive prediction error in the last in-sample period. If that error can be presumed to be an ephemeral chance excess, then the adopted ARIMA model is fortunate in alone avoiding its incorporation in its initial ex-sample forecast. This feature is also evident in Figure 6 where it is evident that the regression model is tending to take the last in-sample observation as a point of departure, and the adopted ARIMA model avoids overstatement by neglecting to do so. However, while this feature is obviously critical to the initial poor performance of the alternative ARIMA model, it plays only a modest role in that of the regression model.

The more noteworthy observation in terms of the performance comparison is that among the last four quarters of the ex-sample performance all three models perform comparably well, and more distant forecasts are generally a better guide to the robustness of model forecasts. In general, therefore, resort to the regression model for forecasting ex-sample developments seems to involves no considerable loss of accuracy compared to simple time series models.

8. Conclusion

We have found evidence of a long-run relationship between the volume of delinquent consumer credit and the volume of consumer debt outstanding, optimism and the interest rate on personal loans. We have also found long-run relationships between default rates for credit cards, and other consumer loans, and disposable income, interest rates, and optimism and a relationship between default rates on residential real estate loans, the personal loan rate, disposable income and optimism. These findings are consistent with a number of explanations including that when debt increases so does the riskiness of institutions' loan portfolios, that adverse selection is present and that when people are more optimistic and perhaps intend to borrow in the future they are more careful to keep up their repayments. The positive (conditional) time trend in delinquency rates is consistent with reduced stigma being attached to delinquency over time, which is consist with the findings of Gross and Souleles (2002). We did not find evidence that supported the strategic default hypothesis when we considered residential loans on real estate. The delinquency rates in consumer loans markets adjusted to their long-run equilibrium values much more quickly than delinquency rates for real estate debt. We estimated short-run dynamic models which showed that current changes in the independent variables often had different effects compared to lagged changes. We examined the volume of delinquent consumer credit and found that the short-run dynamic model gave forecasts that were comparable to those of an ARIMA model. Finally we simulated the effects of a two standard deviation shock to each of disposable income, interest rates, volume of debt and optimism, in turn, on delinquency volume. All of the variables showed the expected time path except for disposable income. The effect of a shock to the latter suggested that if disposable income increases borrowers tend to borrow more than they can service.

Table 9: ARMA models for first differences of log-transformed variables

	Benchmark Forecasting Models				*Forecasting Models for Predictor Variables*							
	Alternative Δ[ln(rdelsa)]		Adopted Δ [ln(rdelsa)]		Interest Rate Δ [ln(insa)]		Credit Δ [ln(rccoutsa)]		Income Δ [ln(rpdisa)]		Sentiment Δ [ln(sent)]	
Performance:												
Std error	.027666		.027617		.018655		.011237		.008004		.026298	
Log likelihood	137.408		136.481		163.071		193.405		216.180		140.042	
AIC	–266.815		–266.962		–318.141		–376.810		–426.360		–274.083	
SBC	–258.243		–260.532		–309.569		–366.095		–419.931		–267.654	
Estimates:	*Coeffic*	*t-stat*	*Coeffic*	*t-stat*	*Coeffic*	*t-stat*	*Coeffic*	*t-stat*	*Coeffic*	*t-stat*	*Coeffic*	*t-stat*
Constant					–.003456	–1.590	.004305	2.1857*	.007127	8.008**		
AR1:	.206711	1.401			.117425	.928	.485741	3.8981**	–.797317	–4.047**		
AR2:	.468304	2.936**	.581118	4.100**	.234019	1.763	.280024	2.1573*				
AR4	–.260310	–1.802	–.274847	–1.905								
MA1:									–.584486	–2.205*	.355898	3.075**
MA2:												
MA10:											–.344268	–2.716**
MA12:	.384081	2.091*	.461147	2.677**			.510320	2.9371**				
SMA1:					.419466	2.984**	.462836	3.2896**			.465688	3.847**
Box-Liung Prob:												
At lag 16	.869161		.807202		.874106		.987947		.671355		.943370	
Min by lag 16	.792693		.339991		.872596		.593673		.495791		.572957	
At lag 24	.704612		.676723		.950182		.949631		.804073		.974700	
Min by lag 24	.682284		.339991		.872596		.593673		.495791		.572957	

Note that constants cited above are the non-zero estimated mean value for the series, not the intercept.

Table 10: Comparison of regression forecasts with ARIMA benchmarks

Ex-sample	**Actual Values**	Adopted ARIMA	**Regression Model**	Alternative ARIMA
Forecasts				
2004 Q1	**183.458**	185.380	**199.729**	190.967
2004 Q2	**196.771**	193.533	**196.867**	197.520
2004 Q3	**194.027**	191.914	**196.779**	201.299
2004 Q4	**193.133**	193.780	**196.492**	201.953
2005 Q1	**184.415**	194.172	**198.050**	203.538
Errors:				
2004 Q1		–1.921	**–16.271**	–7.509
2004 Q2		3.238	**–.096**	–.749
2004 Q3		2.113	**–2.752**	–7.272
2004 Q4		–.648	**–3.359**	–8.820
2005 Q1		–9.757	**–13.636**	–19.124
Ex-sample RMSE		4.780	**9.691**	10.520
In-sample RMSE		4.835	**2.222**	4.781

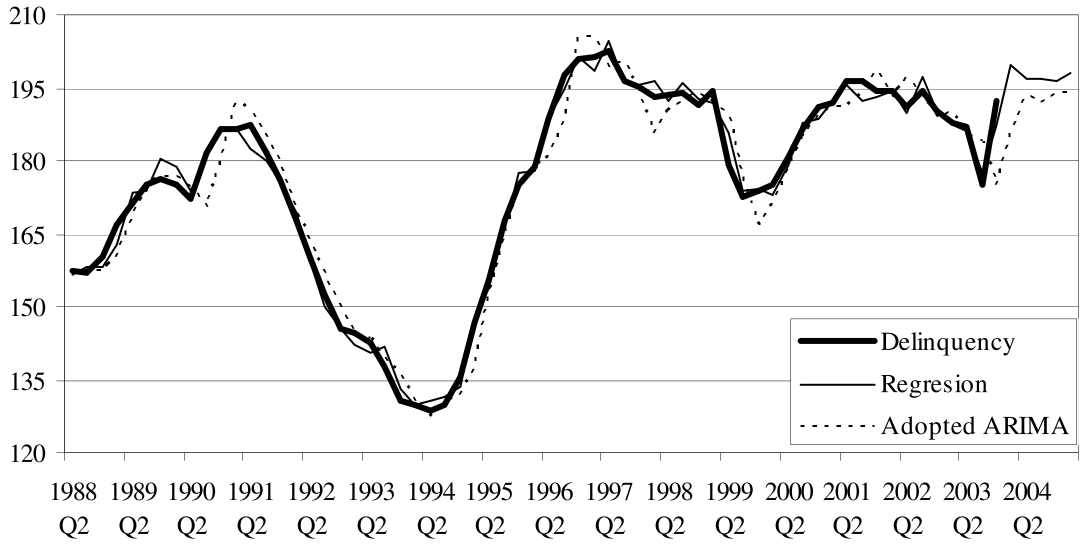


Figure 6: Tracking behaviour of alternative models for delinquency volume.

References

Agarwal, S and Liu, C. (2003) Determinants of credit card delinquency and bankruptcy: macroeconomic factors. *Journal of Economics and Finance 27(1),* Spring. 75-84.

Ausubel, L.M. (1997) Credit card defaults, credit card profits and bankruptcy. The *American Bankruptcy Law Journal*, 71, Spring, 249-270.

Grieb, T, Hegji, C, and Jones, S T. (2001) Macroeconomic factors, consumer behaviour, and bankcard default rates. *Journal of Economics and Finance*, 25(3), Fall, 316-327.

Gross, D and Souleles, N. (2002) An empirical analysis of personal bankruptcy an delinquency. *Journal of Financial Studies*, 15(1), 319-347.

Kau, J. B., Keenan, D.C., and Kim, T (1994) Default probabilities for mortgages. *Journal of Urban Economics*, 35(3), 278-296.

Kau, J. B., Keenan, D.C., and Kim, T (1993) Transaction costs, suboptimal termination and default probabilities. *Journal of the American Real Estate and Urban Economics Association*, 21(3), 247-263.

Lambrecht, B, Perraudin, W, and Satchell, S (1997) Time to default in the UK mortgage market. *Economic Modelling*, 14, 485-499.

Patterson, K (2000) *An Introduction to Applied Econometrics: A Times Series Approach.*

Stavins, J (2000) Credit card borrowing delinquency and personal bankruptcy. *New England Economic Review*, August, 15-30.

Sullivan, A.C. (1987) *Economic Factors Assocaited with Delinquency Rates on Consumer Instalment debt*. Credit Research Center, Working Paper No 55, Krannert Graduate School of Management, Purdue University.

Teo, A.H.L (2004) Delinquency risk in residential ARMs: a hazard function approach. *Journal of Real Estate Portfolio Management*, 10(3), 243-258.

Whitley, J, Windram, R, and Cox, P (2004) *An Empirical Model of Household Arrears.* Working Paper 214, Bank of England.

Definitions of variables

Lnrdelsa	log of (real consumer loan debt outstanding on loans to US chartered commercial banks which is 30+ days over due, in \$00 millions at year at year 2000 prices). Sources of raw data: *Charge off and delinquency rates on loans and leases at commercial banks*, Consumer loans: All. and Series G19 *Consumer Credit* debt outstanding to commercial banks. All series from FRB. Seasonally adjusted by authors using X12,.
Lnccsa	log of (consumer credit card debt to US chartered commercial banks which is 30+ days over due as a percentage of end of period corresponding debt outstanding). Sources of raw data: *Charge off and delinquency rates on loans and leases at commercial banks* , Consumer loans: Credit Cards, FRB. Seasonally adjusted by authors using X12.
Lnosa	log of (consumer non-credit card debt to US chartered commercial banks which is 30+ days over due as a percentage of end-of-period corresponding debt outstanding). Sources of raw data: *Charge off and delinquency rates on loans and leases at commercial banks*, Consumer loans: Other, FRB. Seasonally adjusted by authors using X12.
Lninsa	log of (nominal interest rate on 24 month personal loan). Source of raw data: *Terms of Credit, Consumer Credit Historical Data*, FRB. Seasonally adjusted by the authors using X12.
Lnrccoutsa	log of (sum of revolving and non-revolving consumer credit outstanding to commercial banks in \$00 millions divided by price index personal consumption expenditure seasonally adjusted (2000=100)). Sources of raw data: FRB *Historical Consumer Credit Data, Major Types of Credit* and Bureau of Economic Analysis, *Price Indices for Personal Consumption Expenditures by Major Type of Product* Table 2.3.4. Numerator seasonally adjusted by the authors using X12.
Lnrpdisa	log of (disposable personal income (in \$00 million) seasonally adjusted divided by price index personal consumption expenditure seasonally adjusted (2000=100)). Sources of raw data: *Price Indices for Personal Consumption Expenditures by Major Type of Product*, Table 2.3.4 and *Personal Income and its Disposition*, Table 2.1, Bureau of Economic Analysis.
Lnsent	log of index of relative expected change in financial situation in one year's time relative sentiment. Source: Index of Consumer Sentiment, Table 6 Expected Change in Financial Situation*, Index of Sentiment, Surveys of Consumers*, Institute for Social Research, University of Michigan. Seasonally adjusted by the authors using X12.

Lnrhpsa	log of (US combined house price index seasonally adjusted / price index personal consumption expenditure seasonally adjusted (2000=100)). Sources of raw data: *OFHEO House price index, US Combined Index*: Office of Federal Housing Enterprise Oversight Office*; Price Indices for Personal Consumption Expenditures by Major Type of Product*, Table 2.3.4, Bureau of Economic Analysis. OFHEO House price index seasonally adjusted by the authors using X12.
Lnrnoutsa	log of (real estate loans outstanding to Commercial Banks /price index). Source: Series bcablcr_ba.m, *Federal Reserve Board*. Numerator seasonally adjusted by the authors using X12.
Lnmisa	log of (nominal interest rate on conventional conforming 30 year fixed rate mortgages). Source: *Primary Mortgage Market Survey*, Freddie Mac. Seasonally adjusted by the authors using X12.
Lnccinsa	log of (nominal credit card interest rate). Source: Consumer Credit G19, Terms of Credit, *Federal Reserve Board*. Seasonally adjusted by the authors using X12.
Lndsrsa	Log of (debt service ratio). (Ratio of household debt payments to disposable personal income). Source: *Federal Reserve Board.* Seasonally adjusted by FRB.

All seasonal adjustments performed before logs were taken.